

A Neuro-Fuzzy Approach based Performance Improvement of Reliable Routing Scheme in Vehicular Ad -Hoc Network

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ABSTRACT: Vehicular Ad-hoc network (VANET) has become the key research study due to increasing demand of road safety and management. VANET is a subclass of Mobile Ad-hoc NETWORK (MANET) which belongs to a family of Wireless Ad-hoc network (WANET). The main motive of this research work is to perform an assortment of vehicular nodes that act as mobile hosts establish a transient network without the assistance of any centralized administration or any established infrastructure. This paper proposed a neuro-fuzzy approach based performance improvement of reliable routing scheme in vehicular ad-hoc network. Simulation is performed using MATLAB software. The Simulation results show that the proposed algorithm approach gives the considerable and significant better result.

KEYWORDS: VANET, MANET, Neuro, Fuzzy, MATLAB, Routing.

I. INTRODUCTION

VANET is a subclass of Mobile Ad-hoc NETWORK (MANET) which belongs to a family of Wireless Ad-hoc network (WANET). Talking of MANET, it is basically a self organizing communication system that is not dependent on any infrastructure. Moreover, according to the survey, most of the accidents can be avoided if driver gets the warning half a second before an accident. VANET is serving the said purpose by sharing road safety and traffic analysis information through internet. The VANET architecture consists of vehicle and infrastructure components. Vehicle workings consist of the On Board Unit (OBU) and the application that will be working for OBU to enable it to communicate. Moreover, infrastructure components consist of RSUs commonly connected to the internet. VANET is quite different from other ad-hoc networks in terms of features such as high mobility, abrupt changes of topology, time critical, high computational ability etc. Besides its good features and applications there are some challenges also linked to the said network such as security, scalability, quality of service, power control etc.

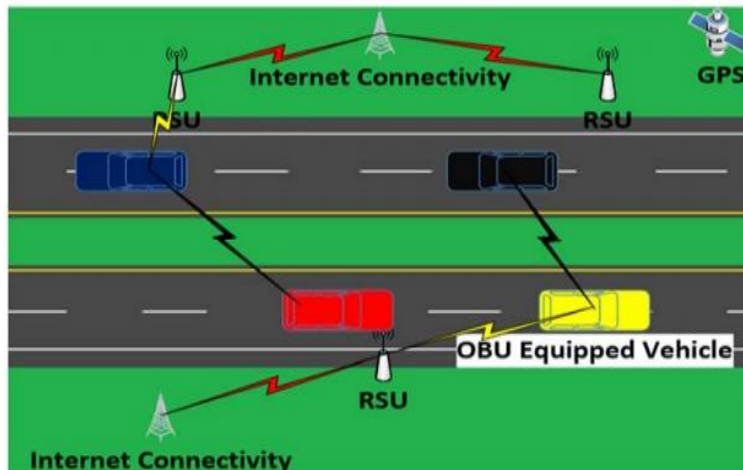


Figure 1: VANET System Architecture

Figure 1 is showing VANET system architecture. In VANET, there are mainly two kinds of communication such as Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I). V2V is a wireless communication between the vehicles where as V2I is the communication between the vehicle and infrastructure.

II. BACKGROUND

Z. Khan et al., [1] In vehicular ad hoc networks (VANETs), communication links break more frequently due to the high-speed vehicles. In this paper, a novel cluster-based VANET oriented evolving graph (CVoEG) model is proposed by extending the existing VoEG model to improve the reliability of vehicular communications. Here, the link reliability is used as a criterion for cluster members (CMs) and cluster heads (CHs) selection. The proposed CVoEG model divides VANET nodes (vehicles) into an optimal number of clusters (ONC) by using Eigen gap heuristic. In a given cluster, a vehicle will be selected as a CH, if it has a maximum Eigen-centrality score.

D. R. Chowdhury et al., [2] The vehicles of the road where the incident happened, or the vehicles of roads which are connected to incident location by nearby junctions, are most affected and hence are more relevant to receive the SM as fast as possible. Hence, this study proposes a novel method to predict the relevance of vehicles using a distributed algorithm and heuristically tries to disseminate SM toward the relevant vehicles. The authors have compared their work with three state-of-the-art algorithms and found that vehicular relevance-based data dissemination is compatible with the existing algorithms on the metrics of packet loss and dissemination delay, but clearly leading in the metric of relevant dissemination.

A. A. Kashani et al., [3] In this method, the source vehicle employs the packet advancement, vehicle density, and packet delivery probability as parameters for determining the appropriate vehicle as to the next hop. The number of vehicles participating in forwarding the packets is optimised using trust-based calculations. In addition, the source vehicle can schedule a set of relay nodes based on their degree of trust. Highway environment simulations suggest that compared to other published methods in the literature, the proposed method can improve routing performance in terms of all quality-of-service metrics.

L. L. Cárdenas et al., [4] This probability is computed based on four designed metrics: distance to destination, node's position, available bandwidth and nodes' density. Furthermore, an improved version of ProMRP called EProMRP is also proposed. EProMRP includes an algorithm that accurately estimates the current position of nodes in the moment of sending the packet instead of using the last updated position obtained from the previous beacon message. Simulations are carried out in a realistic urban scenario using OMNeT++/VEINS/SUMO, including real maps from the OpenStreetMaps platform. Simulation results show a better performance of ProMRP and EProMRP compared to recent similar proposals found in the literature in terms of packet losses and end-to-end packet delay, for different vehicles' densities.

Y and S. Shrivastava et al., [5] Major concern of industry is to design suitable inventory model. Some of the existing inventory management research work are discussed in literature. But this field is still a big area of interest. Many research works used artificial intelligence models for inventory management. Therefore, this paper uses the current and past employees' data to analyze attrition behavior of employees and to provide bonus/promotion to employees having non attrition behavior by using PSONN and fuzzy rules. The result shows that the efficiency of model is improved with respect to existing methods by approximately 2%.

C. Zhang et al., [6] The signature verification method for safety message can both achieve computation efficiency by reducing the number of computation operations of bilinear pairing and resist impersonation attack by using tracking key implement. GSK is associated with the forward and backward keys and is only shared among unrevoked vehicle within a group. Performance analysis and simulations demonstrate that our protocol can provide promising security against various common types of attackers and is more efficient than traditional group-signature-based authentication protocols, in terms of computation time cost, authentication delay and message loss rate.

S. Hao et al., [7] propose a stable and energy-efficient routing algorithm, based on learning automata (LA) theory for MANET. First, we construct a new node stability measurement model and define an effective energy ratio function. On that basis, we give the node a weighted value, which is used as the iteration parameter for LA. Next, we construct an LA theory-based feedback mechanism for the MANET environment to optimize the selection of available routes and to prove the convergence of our algorithm. The experiments show that our proposed LA-based routing algorithm for

MANET achieved the best performance in route survival time, energy consumption, energy balance, and acceptable performance in end-to-end delay and packet delivery ratio.

L. Tang et al., [8] One of the challenges posed by the study of vehicular *ad hoc* networks (VANETs) is the transmission of data issued by valued traffic information services under incomplete link conditions. Many dissemination protocols have been developed by the community to solve the issue. In this survey, the authors explore the service discovery where data dissemination should serve as a foundation. Then, they propose an overview and taxonomy of a large range of data dissemination available for VANETs. Finally, they illustrate the simulation infrastructure by collaborating two independent simulators. The objective is to provide guidelines to easily understand and extend the capabilities of protocols according to the users' needs.

P. Verma et al., [9] This eventually leads to the selection of a vehicle-ID-based random back-off number, mitigating all possible probabilities of collision due to same back-off number selection. The simulation is performed considering saturated traffic conditions, to analyse its behaviour under most critical situations. The proposed model eliminates the chances of selecting zero as the initial back-off number, eliminating any chances of consecutive freeze process. The proposed one-dimensional Markovian model is validated by MATLAB. The proposed model provides a clear depiction that it performs better than the traditional IEEE 802.11OCB used for VANET. Also, it is worth noting that the achieved results outperform the existing work in terms of average packet delay since nearly one-fourth of the contention window size is utilised throughout the simulation.

III. PROPOSED METHODOLOGY

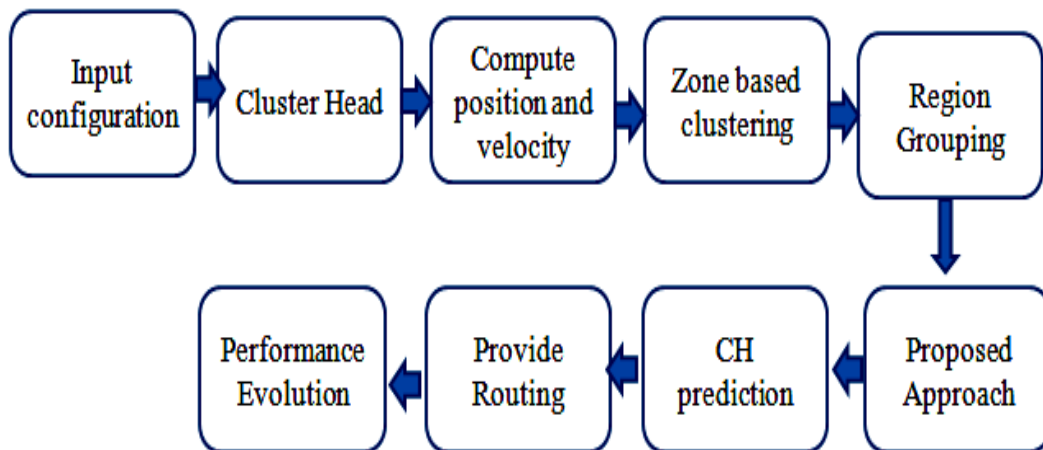


Figure 2: Flow Chart

Neuro-Fuzzy prediction:

In previous step, CH selects made by clustering Algorithm. After k- time zone update & validate of CH also important. For creation of this model, we create Neuro-Fuzzy prediction method. At first fuzzy based membership function will be created we have to Gaussian –bell shape membership function is used for more information. For efficient creation of rules, Neuro-fuzzy model based training sample acquired by initial clustering Algorithm (4.2).

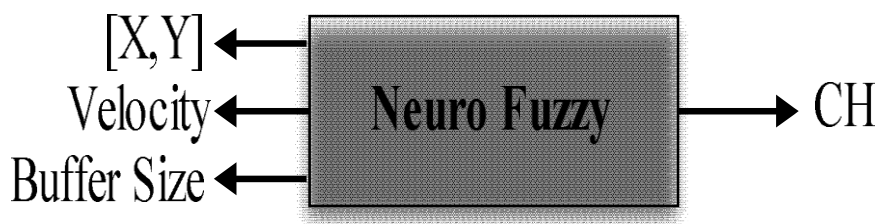


Figure 3: Neuro Fuzzy

In Neuro-Fuzzy given i/p for node position [X,Y], Velocity Buffer size of vehicle. A self learning mechanism is nothing but the fuzzy rules are created by initial clustering algorithm. So we don't need any additional training Neuro-Fuzzy easily turning depend upon initial condition nodes.

Based on training data fuzzy rules create and updated. Totally we use 40 iteration for minimum training error inneuro-fuzzy. This updated neuro-fuzzy engine called as self- learning CH predictor. After the vehicle/node movement in each zone, our CH predictor, predict the particular node CH or not. It's a fast process, so CH formation delay also very less. All details explained in Algorithm 3

Algorithm:

(Neuro-Fuzzy Training)

I/p: i) Node member with Centroid value

ii) Membership function model of Fuzzy

O/p: Rule Prediction

a) Initialize zones and compute

P_{ch} - Percentage of CH

$P_{CHzones} = \text{Total no. Of nodes in particular zone} / \text{Total nodes}$

b) Neural N/w used for Training the Fuzzy Model

$y_{ik} = f(n, D_{ik})$

c) Rules Creation by using Neural N/w

d) Predicted rules

Routing:

After CH formation & validation the data communicate to source to destination. Initially compute the distance b/w each CH to CH distance and velocity the distance is greater their sensor radius we have assign the link reliability is infinite. Apply proposed algorithm for routing, so we consider both like forward and backward searching. The routing path estimated with minimum cost.

IV. SIMULATION RESULTS

The implementation of the proposed algorithm is done over MATLAB 9.4.0.813654 (R2018a). The signal processing toolbox helps us to use the functions available in MATLAB Library for various methods like GA, NN, PSO etc.

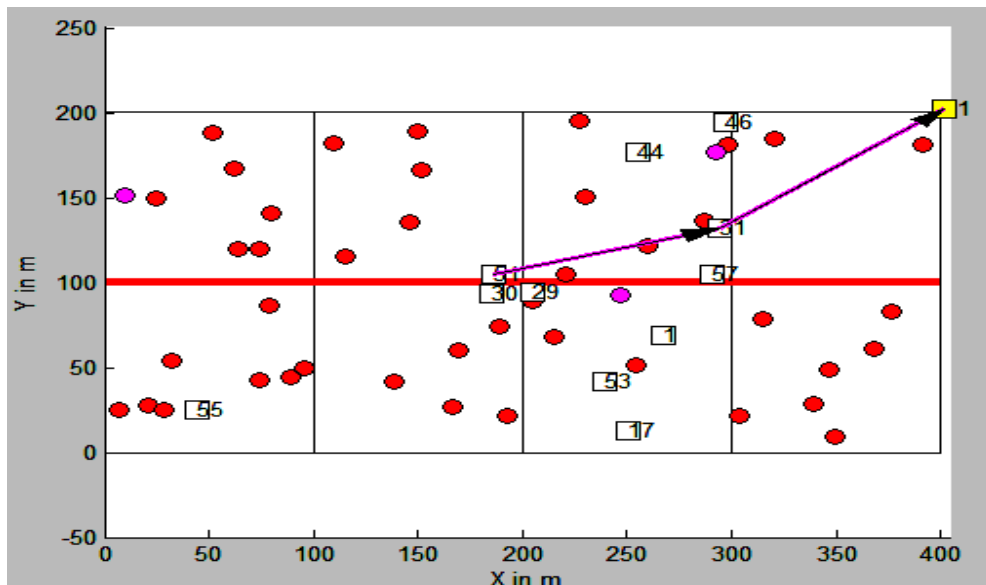


Figure 4: Route update

In Fig 4 Totally we have 60 nodes to show, the cluster Head change due to node high mobility. The mobility of nodes CH selects and update in each zone by using Neuro-Prediction method. The find routing path also displayed.

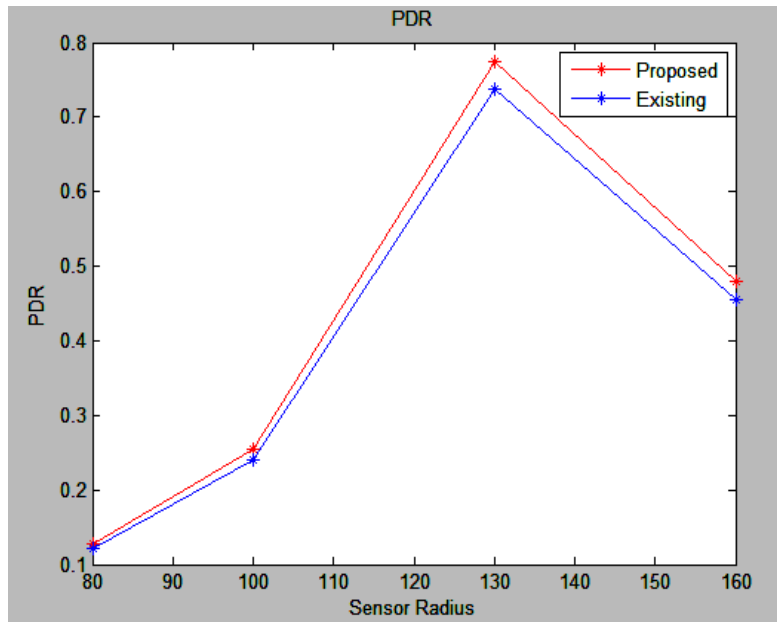


Figure 5: Packet delivery ratio

The figure 5 compares the Packet Delivery Ratio (PDR) with sensor Radius. If the sensor radius is low, the communication path breakage maybe happen , so it's automatically reduce the PDR if sensor.

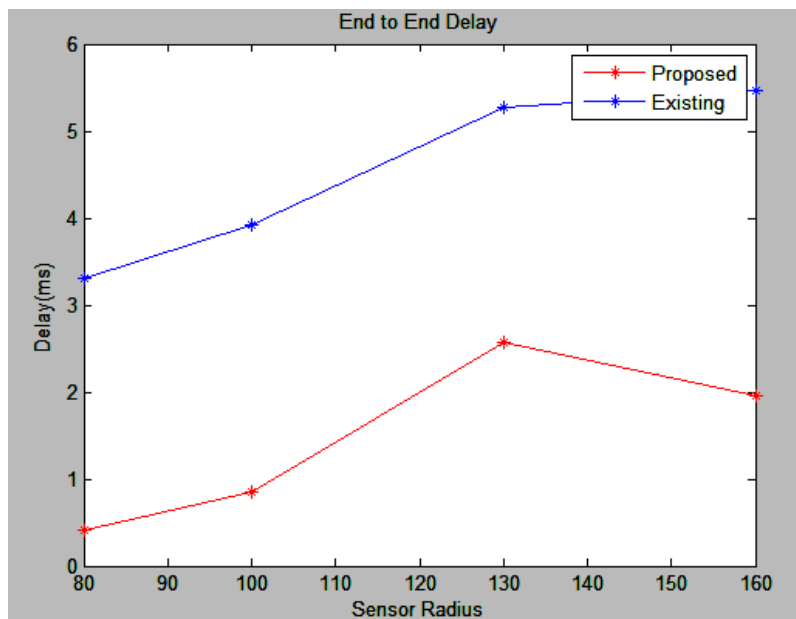


Figure 6: End to End delay

End to End delay varies based on sensor radius. The sensor Radius in low value, the path breakage may ne happen. So normally in low sensor radius End to End delay is high .When sensor radius increases the End to End decreases compare to exiting method proposed method have low End to End delay.

Table 1: Comparison of proposed and previous work

Sr. No	Parameters	Previous Work	Proposed Work
1	Method	Unsupervised Cluster	Neuro-Fuzzy
2	Delay	0.01 Sec	0.003 Sec
3	Packet Delivery Ratio	55%	80%
4	No of nodes	50	60
5	Simulation Time	350 Sec	150 Sec

The proposed algorithm is based on neuro-fuzzy while previous it is based on the unsupervised clustering. Simulated results shows that the proposed work result is better than previous work so Neuro-fuzzy approach is considerable and significant result is achieved.

V. CONCLUSION

Research in vehicular ad-hoc networks has experimented a continuous and important increase during the last years. During the development of the contributions that compose this thesis, several issues attracted our attention and now they constitute future research lines. The proposed algorithm is based on neuro-fuzzy while previous it is based on the unsupervised clustering. The proposed algorithm is based on neuro-fuzzy while previous it is based on the unsupervised clustering. Therefore simulated results shows that the proposed work result is better than previous work so Neuro-fuzzy approach is considerable and significant result is achieved. Achieved is 0.003 sec while previously it is 0.01Sec. The total no of nodes is considered in this work is 60 while previously it is 50. The total simulation time is 150 Sec while previously it is 350 Sec. Therefore it can be said that proposed work giving better results than previous work.

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